



Use of heterogeneous background error covariances accounting for precipitations at convective scale

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Outlines

1. Introduction

- The AROME NWP system at convective scale
- The B matrix representation

2. Use of a heterogeneous B in an inc3DVar

- Calibration of specific B matrices
- Formulation

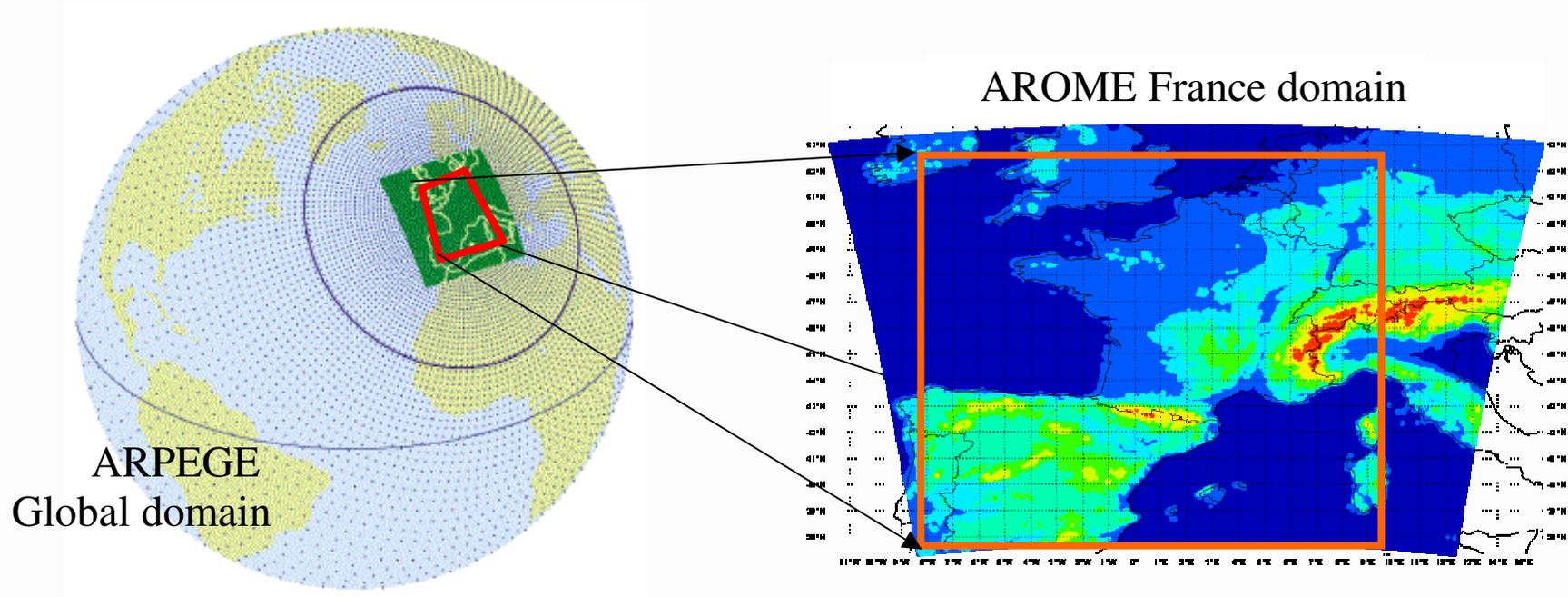
3. Application on real cases

- Impact on analyses
- Reduction of spin-up
- Impact on forecast

4. Conclusions and Perspectives

Introduction: The AROME NWP system

- The non-hydrostatic AROME NWP system became operational at the end of 2008 with a 2.5 km horizontal resolution, allowing realistic representation of clouds, turbulence, surface interactions (mountains, cities, coasts, ...)
- Lateral boundaries are provided by the global ARPEGE model that has a horizontal resolution around 10 km over France



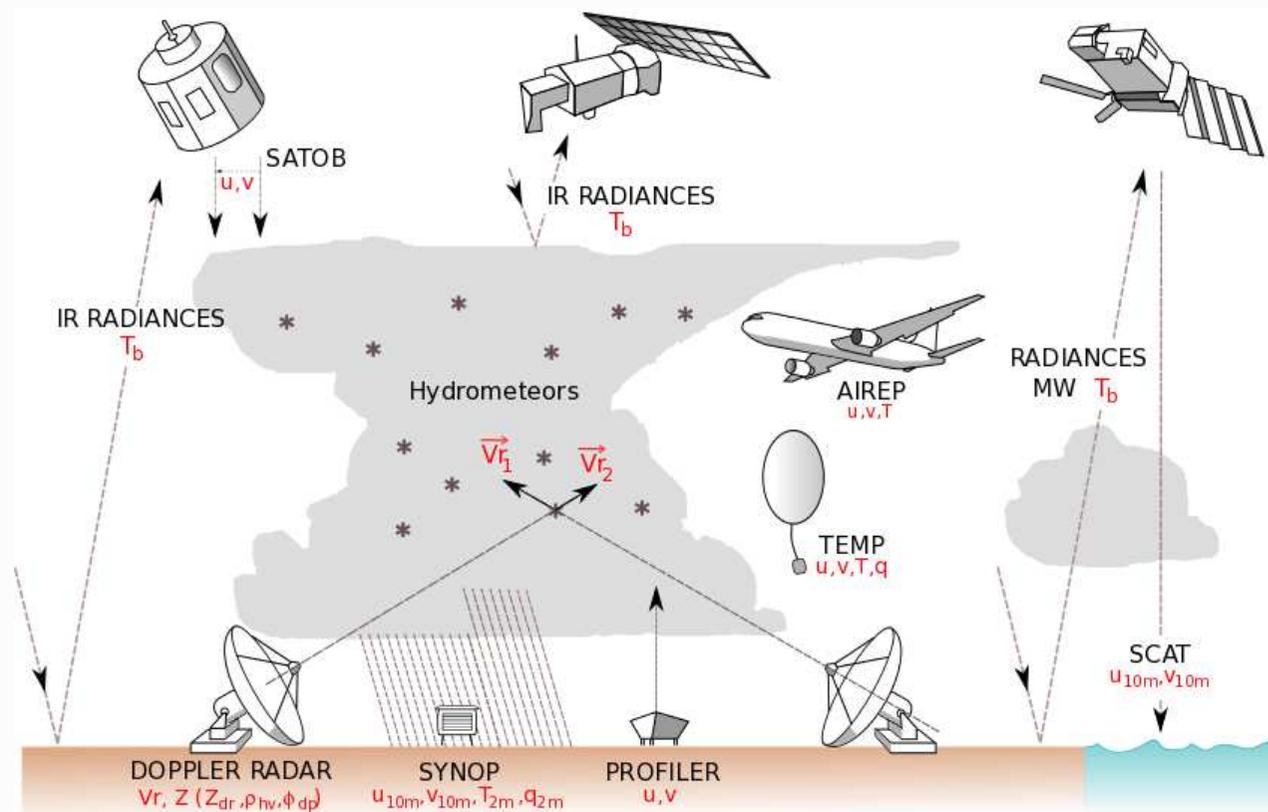
- **Aim** : to improve local meteorological forecasts of potentially dangerous convective events (storms, unexpected floods, wind bursts...) and lower tropospheric phenomena (wind, temperature, turbulence, visibility...).

Introduction: The AROME NWP system

- 3h cycled assimilation/forecast steps, 30h forecasts 4 times per day
- A comprehensive set of various observation types is considered in DA, including satellite radiances and volumic observations of radial velocities and reflectivities from 24 radars:

At convective scale:

- The explicit moist convection allows to consider cloud and rain related observations
- More optimal analysis of variables linked to diabatic processes becomes crucial



⇒ To optimize the use of observations in clouds and precipitation, forecast errors need to be better represented in those areas

Introduction: B in AROME

DA is based on an incremental 3DVar and on the CVT formulation: $\delta x = \mathbf{B}^{1/2} \chi$

Following notation of Derber and Bouttier (1999) : $\mathbf{B}^{1/2} = \mathbf{K} \mathbf{B}_S^{1/2}$

- **K is the balance operator** that aims in taking increments of the model's variable and to output new less correlated parameters on the same grid using balance constraints.

$$\delta x = \mathbf{K} \tilde{\chi}$$

analytical linear balance operator
ensuring geostrophical balance

regression operators that
adjust couplings with scales

$$\begin{pmatrix} \delta \zeta \\ \delta \eta \\ (\delta T, \delta P_s) \\ \delta q \end{pmatrix} = \begin{pmatrix} I & 0 & 0 & 0 \\ \textcircled{MH} & I & 0 & 0 \\ \textcircled{NH} & \textcircled{P} & I & 0 \\ \textcircled{QH} & \textcircled{R} & \textcircled{S} & I \end{pmatrix} \begin{pmatrix} \delta \tilde{\zeta} \\ \delta \tilde{\eta}_u \\ (\delta \tilde{T}, \delta \tilde{P}_s)_u \\ \delta \tilde{q}_u \end{pmatrix}$$

Berre (2000)

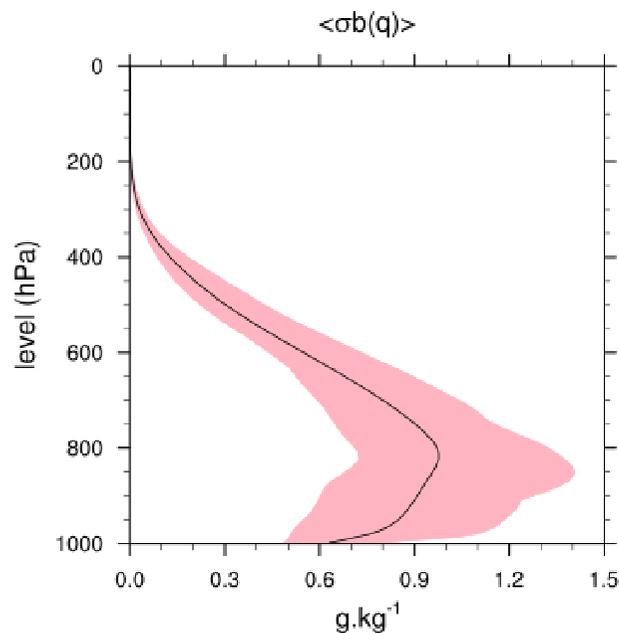
- **B_S^{1/2} is a block diagonal matrix called the spatial transform.** It aims in projecting each parameter onto uncorrelated spatial modes, and then in dividing by the square root of the variance of each mode.

Introduction: limitations of the operational B

AROME uses a climatological B matrix, deduced from statistics performed on differences of forecasts extracted from an ensemble assimilation at convective scale (Brousseau et al. 2011a).

Known limitations for convective scales:

- \mathbf{B}_S is based on the diagonal spectral hypothesis: analysis increments are homogeneous and isotropic
- Forecast errors strongly depend on weather regimes (Brousseau et al, 2011b)



**Spread of daily
forecast error of**

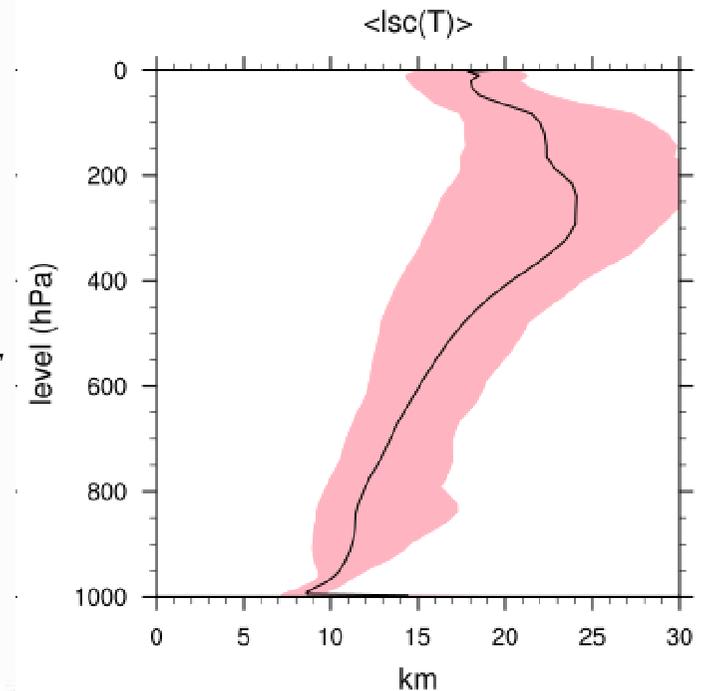
std deviations for q



Correlation lengths for T



*(ensemble gathering
anticyclonic and
perturbed situations)*



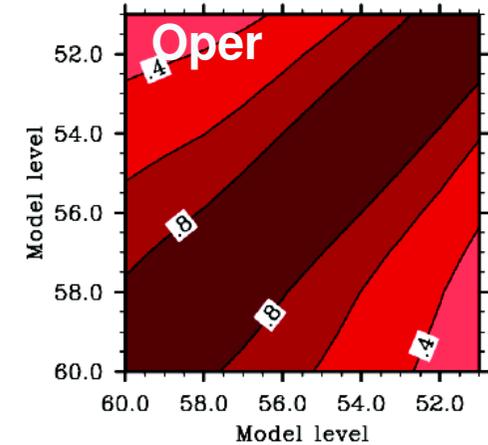
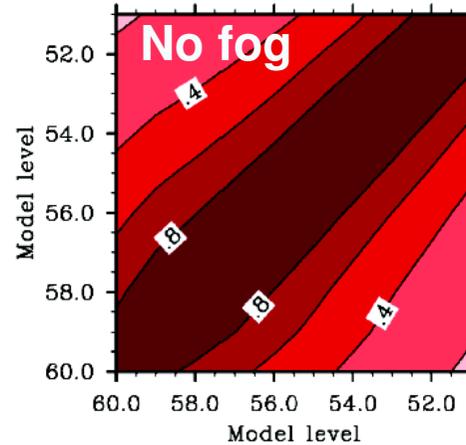
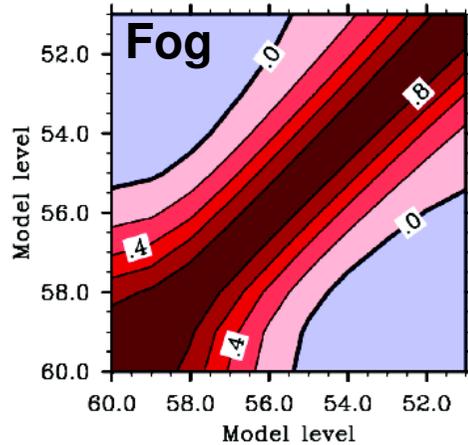
Introduction: limitations of the operational B

- Using geographical masks applied in an ensemble assimilation, it has been shown that structure functions are unsuited for meteorological phenomena that are under-represented in the ensemble (such as fog, clouds, precipitation...)

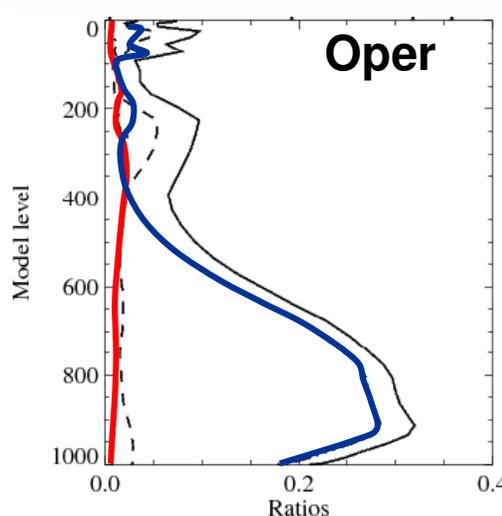
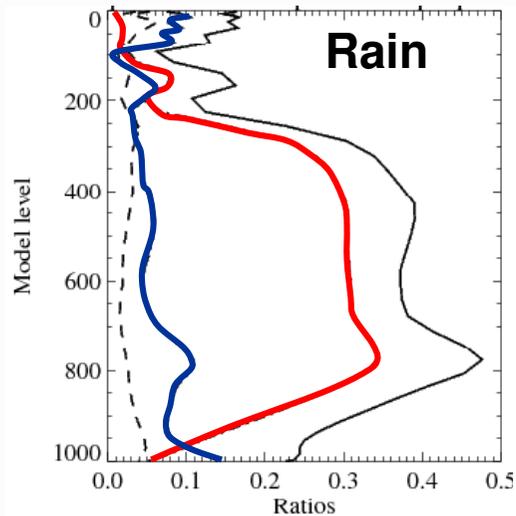
Vertical autocorrelations for T

(zoom in the first 500m)

⇒ Vertical stability of fog



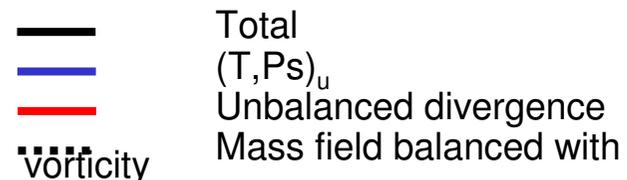
Ménétrier and Montmerle (2011)



Fraction of explained q variance ratios

⇒ Very strong coupling between q and the divergence in precipitating area

Montmerle and Berre 2010





Introduction: limitations of the operational B

⇒ **Flow dependency is obviously needed.** At MF, different solutions are considered:

- by modulating AROME's unbalanced covariances using filtered information deduced from the AEARP
- by filtering background error variances and horizontal correlations calibrated from a daily ensemble assimilation AEARO, mimicking at first what is done in the AEARP at global scale (see posters of Loïk Berre and Hubert Varella). For the time being, such ensemble is unaffordable because computational cost. Tests are ongoing on idealized framework (see Benjamin Ménétrier's poster).

The common point of these approaches is that **a certain degree of flow dependency is brought only to the spatial transforms of B, not to the balance operator.**

An alternative could be to use **the heterogeneous formulation that allows to apply forecast errors representative of one particular meteorological phenomena specifically where this phenomena is observed.**

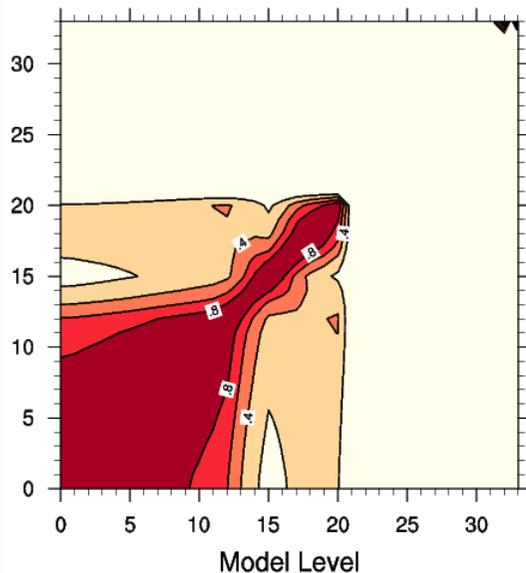
These forecast errors can be climatological or calibrated from the AEARO

Use of a heterogeneous B in an inc3DVar

1st Step: Computation of forecast errors for one particular meteorological phenomena by using bidimensional geographical masks deduced from the background perturbations.

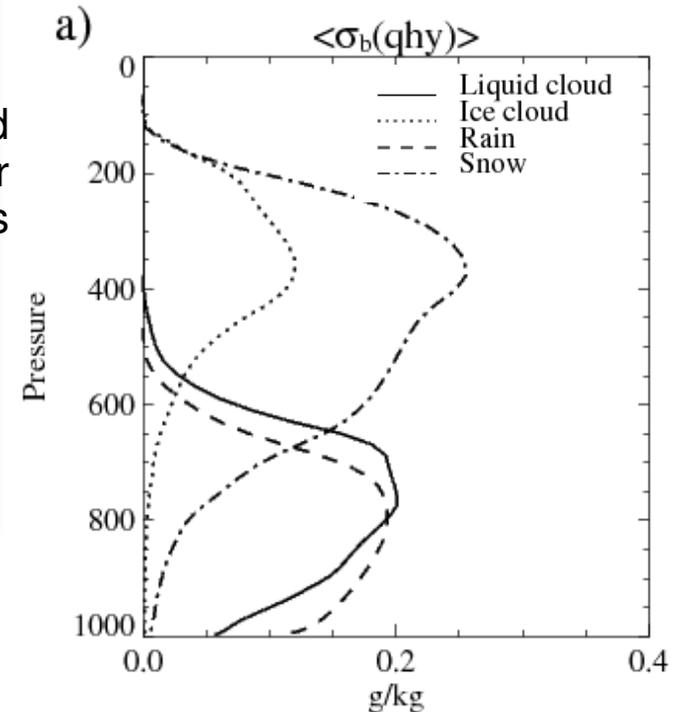
For rain, these masks are defined by thresholding the vertical averaged rain content. At mesoscale, this method has been used to calibrate forecast error covariances for cloud and rain water contents by Michel et al. (2011) and also for other hydrometeors in AROME.

Vertical auto-correlations for rain



Spectrally averaged
standard deviations for
hydrometeors

Rain falling below
the freezing level,
some rain in
convective towers



Use of a heterogeneous \mathbf{B} in an inc3DVar

2nd step: Simultaneous use of different \mathbf{B} matrices using the heterogeneous formulation (Montmerle and Berre, 2010)

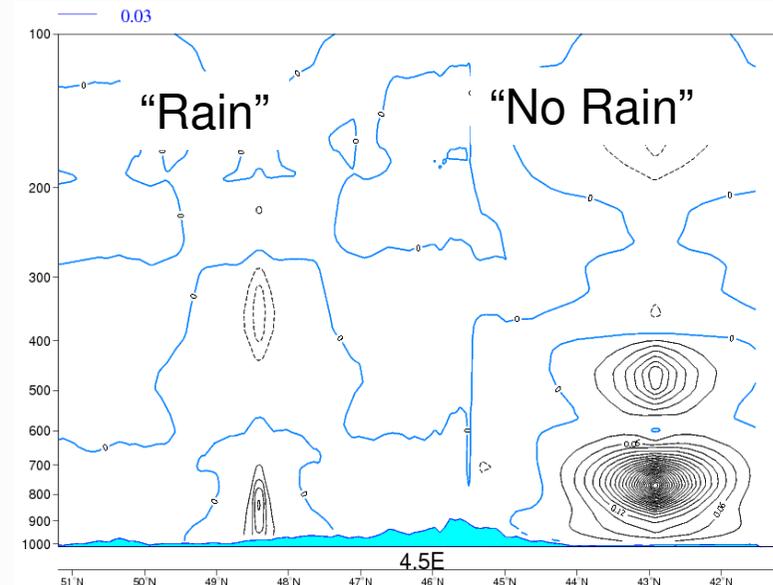
$$\delta x = \mathbf{B}^{1/2} \chi = \begin{pmatrix} \mathbf{F}_1^{1/2} \mathbf{B}_1^{1/2} & \mathbf{F}_2^{1/2} \mathbf{B}_2^{1/2} \end{pmatrix} \begin{pmatrix} \chi_1 \\ \chi_2 \end{pmatrix}$$

Where \mathbf{F}_1 and \mathbf{F}_2 define the geographical areas where \mathbf{B}_1 and \mathbf{B}_2 are applied:

$$\begin{cases} \mathbf{F}_1^{1/2} = \mathbf{S} \mathbf{D}^{1/2} \mathbf{S}^{-1} \\ \mathbf{F}_2^{1/2} = \mathbf{S} (\mathbf{I} - \mathbf{D})^{1/2} \mathbf{S}^{-1} \end{cases}$$

\mathbf{S} and \mathbf{S}^{-1} are direct and inverse Fourier transforms, \mathbf{D} is a binary grid point mask convolved with a normalized gaussian kernel to allow the spread of covariance functions across the sharp transition between 0 and 1

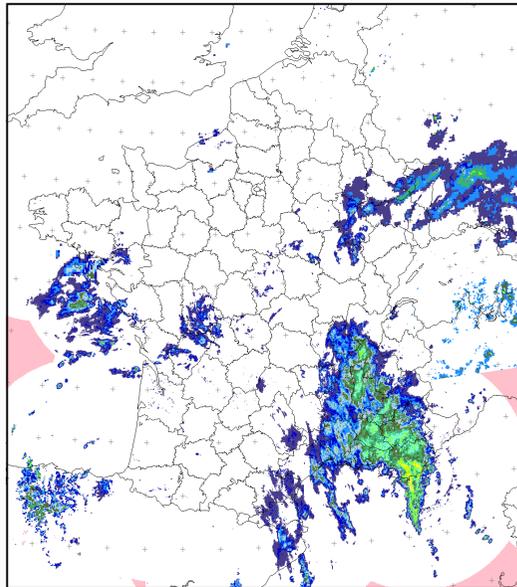
⇒ The size of the CV and of the gradient of the cost function has to be doubled



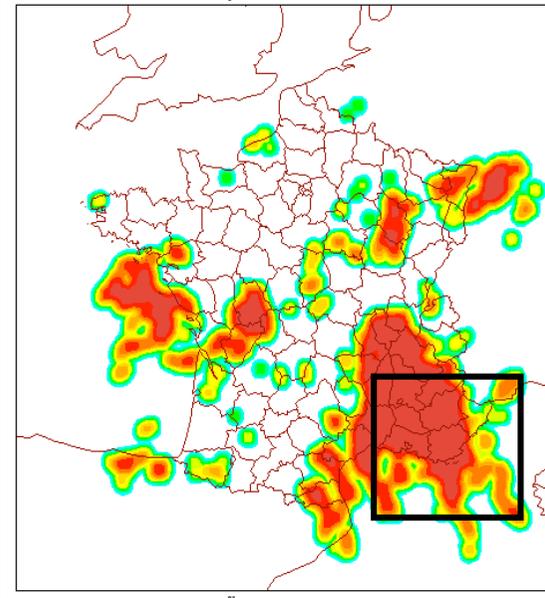
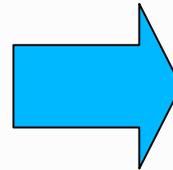
*Vertical Cross section of q increments
4 obs exp: Innovations of -30% RH
At 800 and 500 hPa*

Application on real cases

- \mathbf{B}_1 is the “rainy” forecast error covariance matrix computed in *Montmerle and Berre (2010)*, \mathbf{F}_1 makes use of the reflectivity mosaic produced from the 24 French radars.



*Radar mosaic
15th of June 2010 at 06 UTC*



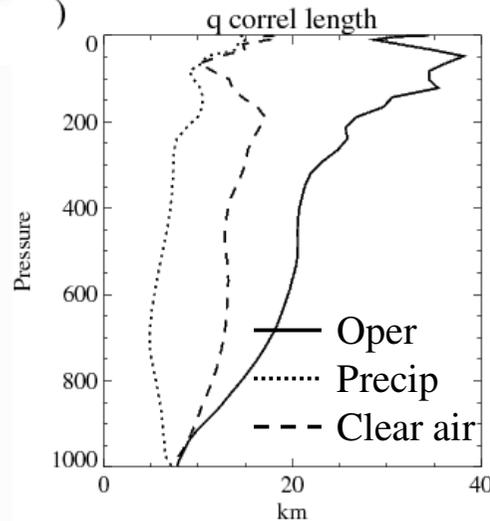
*Resulting gridpoint mask (0 and 1 are
displayed in white and red respectively)*

- In addition to conventional observations, radial velocities and relative humidity profiles, deduced from radar reflectivities using a 1D Bayesian inversion (*Caumont et al., 2010*), are also assimilated in precipitating areas.

Application on real cases: impact on analyses

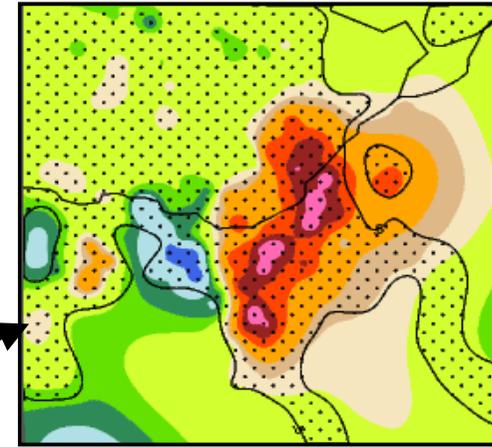
EXP: B_1 =rain, B_2 =OPER, D=radar mosaic
 OPER: B=OPER

Horizontal correlation lengths of the specific humidity q forecast error

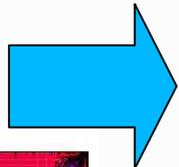


$z = 600 \text{ hPa}$

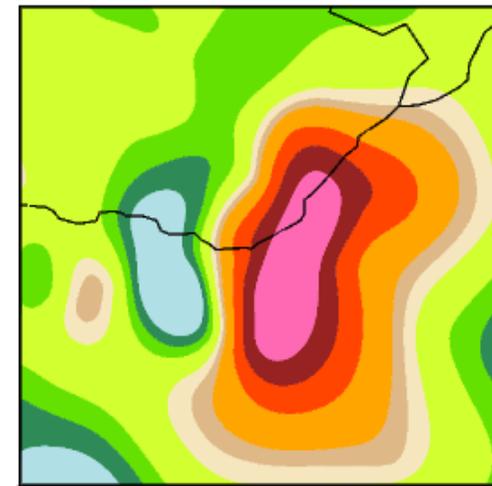
EXP



$D_{ij} > 0.5$

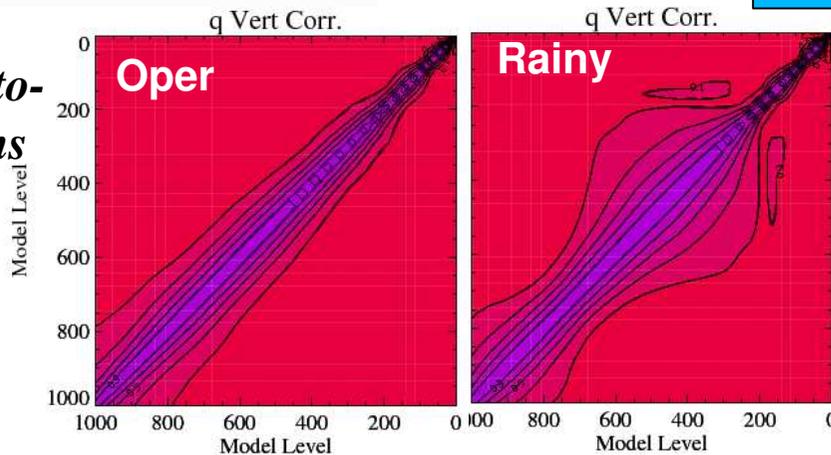


OPER



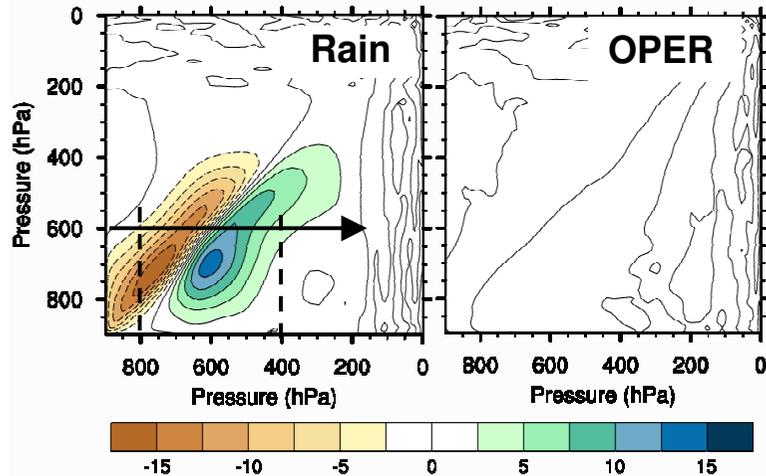
$Inc(q) (g \cdot kg^{-1})$ (zoom)

Vertical auto-correlations for q

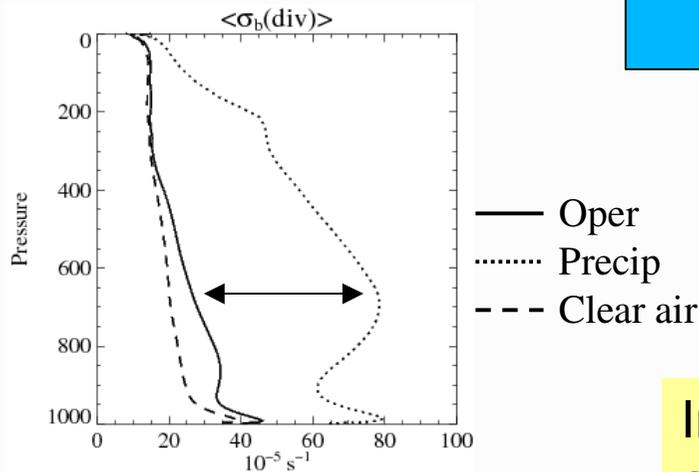


Increments of q (and T), mainly due to the assimilation of reflectivities in mid-tropospheric precipitating areas, are much more localized and more spread vertically in rainy areas for EXP.

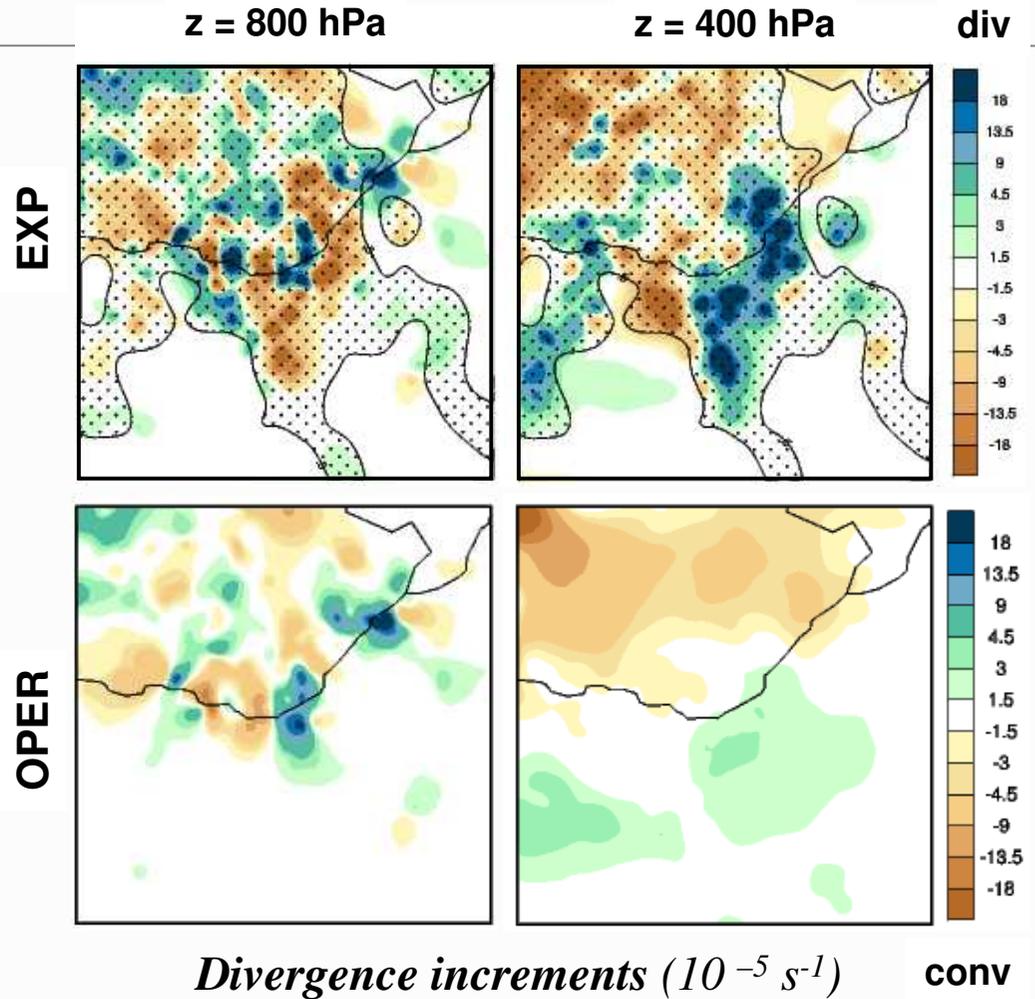
Application on real cases: impact on analyses



Cross covariances between errors of q (y-axis) and div_u (x-axis)



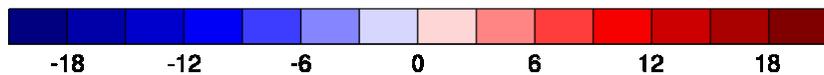
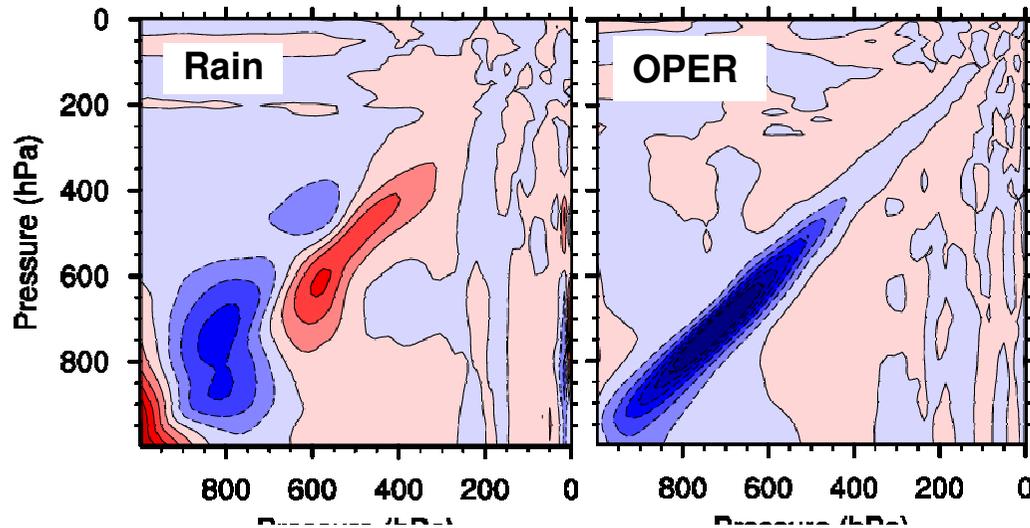
background error standard deviations σ_b for div



Divergence increments ($10^{-5} s^{-1}$) conv

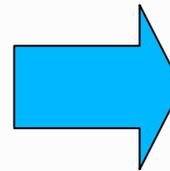
Increments of divergence are more controlled by observations in EXP, and a positive increment of humidity at 600 hPa will enhance convergence below and divergence above in precipitating areas.

Application on real cases: impact on analyses

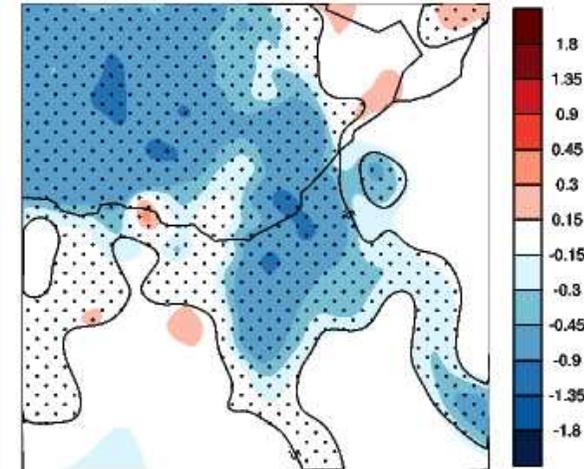


Cross covariances between errors of q (y-axis) and T_u (x-axis) (Unit : $10^{-5} \text{ kg.kg}^{-1}\text{K}$)

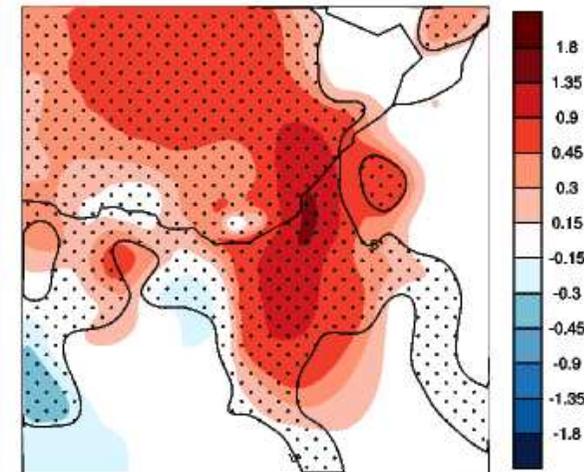
In EXP, mid-tropospheric positive increment of δq will enhance the low level cold pool and the warming in clouds (diabatic effect sampled by the background perturbations)



z = 950 hPa



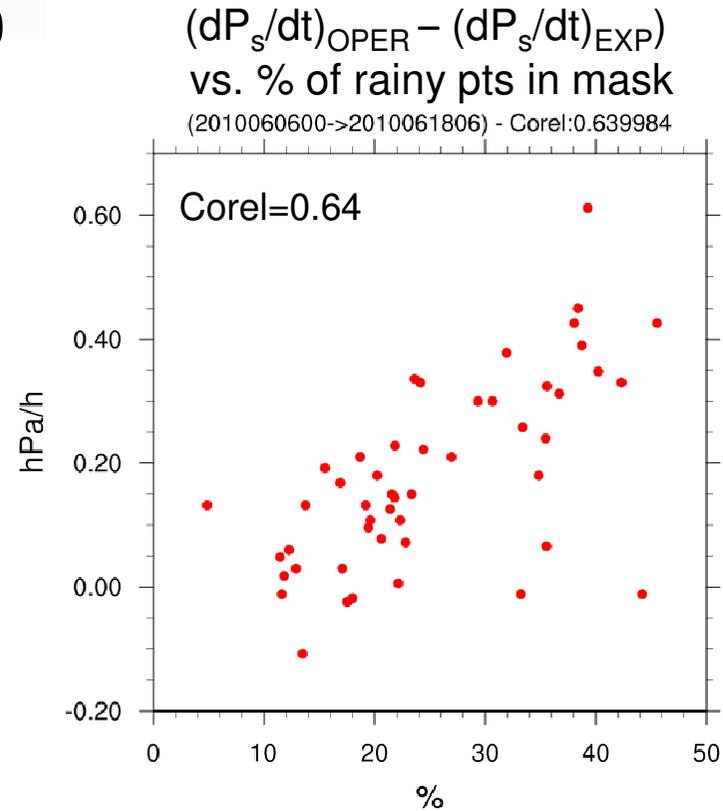
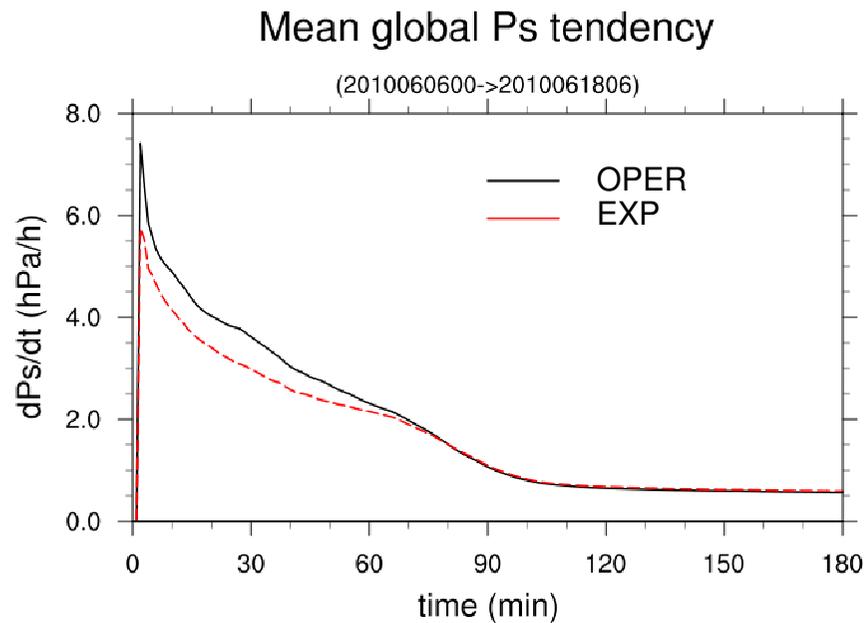
z = 600 hPa



*Horizontal cross sections of the increment difference between **EXP** and **OPER** for temperature T . Units: K.*

Application on real cases: spin-up reduction

Cycled experiment 6 -> 18 June 2010



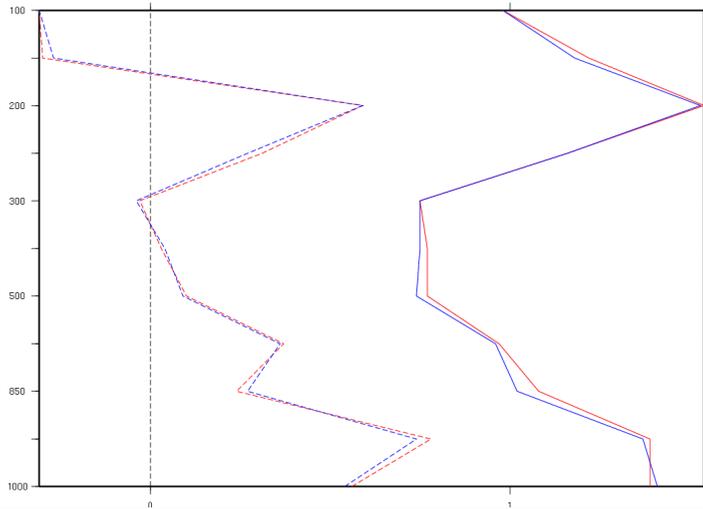
⇒ Imposing more optimal forecast error covariances in precipitations brings a spin-up reduction that is correlated with the number of grid points where these covariances are imposed

Impact on forecasts

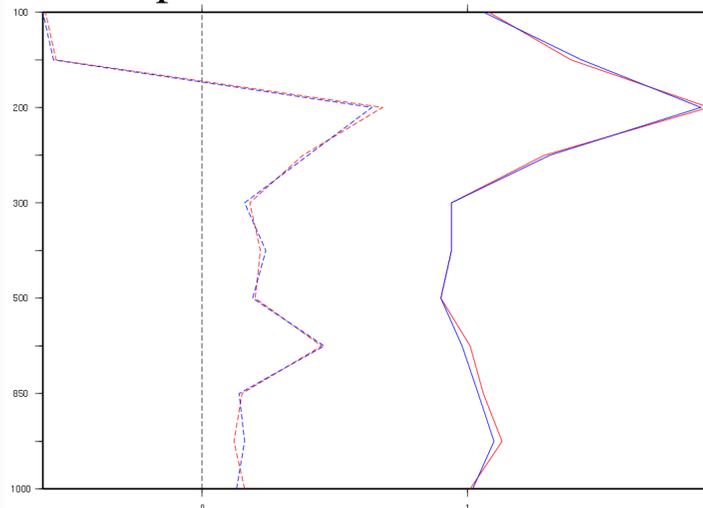
Cycled experiment 6 -> 19 June 2010

Scores against radiosoundings

Mean profiles of 12h forecast for T



Mean profiles of 24h forecast for T

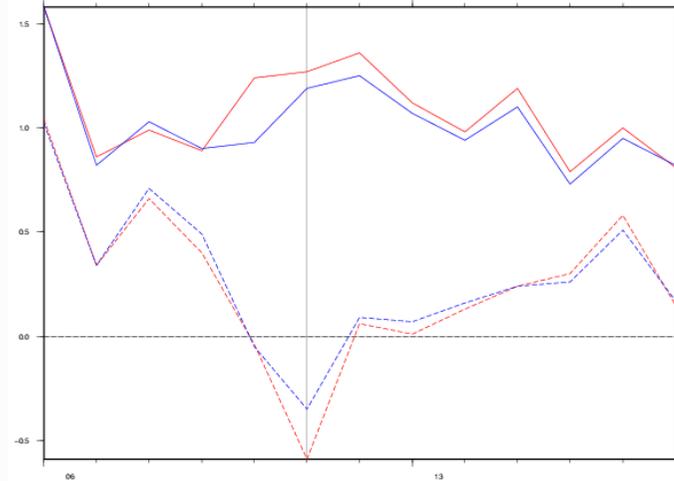


— *Rms error*
..... *Bias*

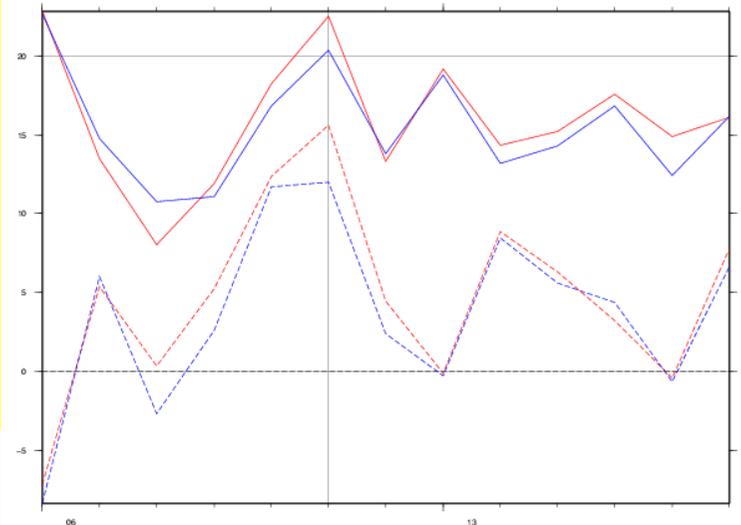
Oper
Exp

⇒ Positive scores against soundings (and ECMWF analyses) in the mid and lower troposphere for T and q, neutral otherwise

time serie of 12h forecast for T_{850hPa}



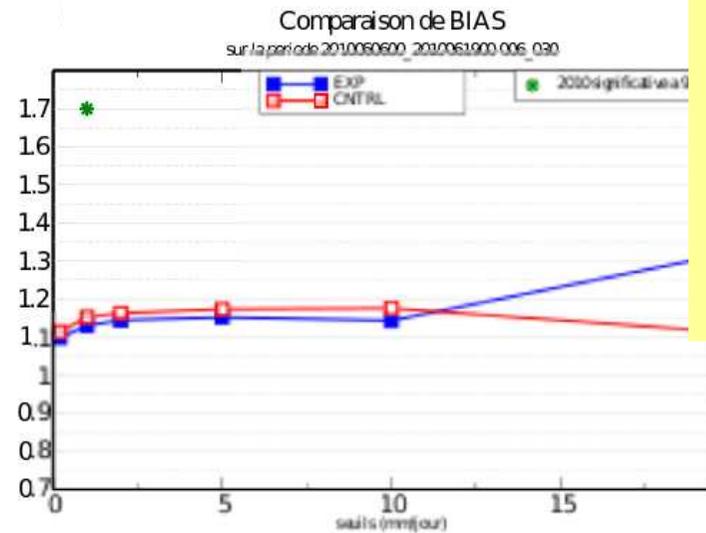
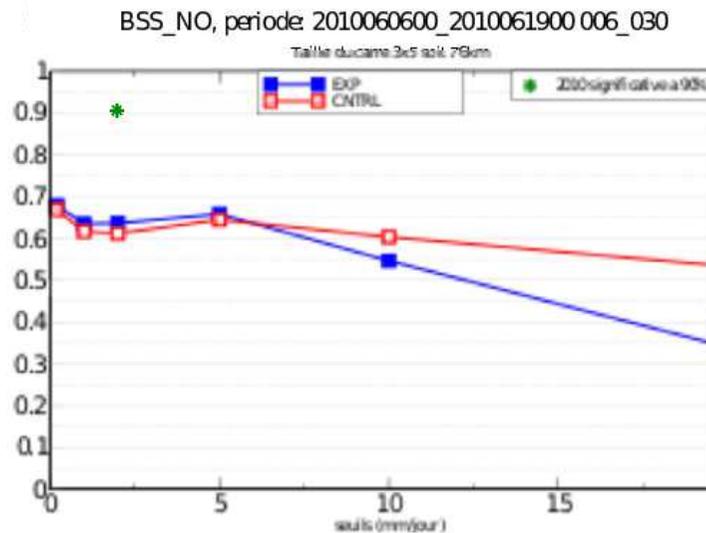
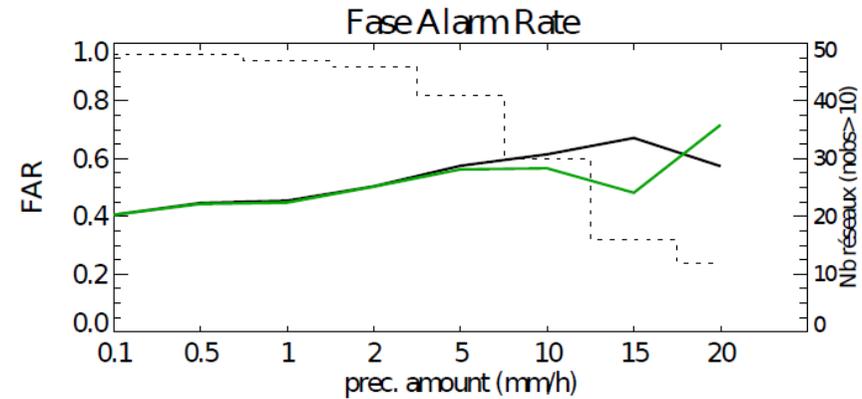
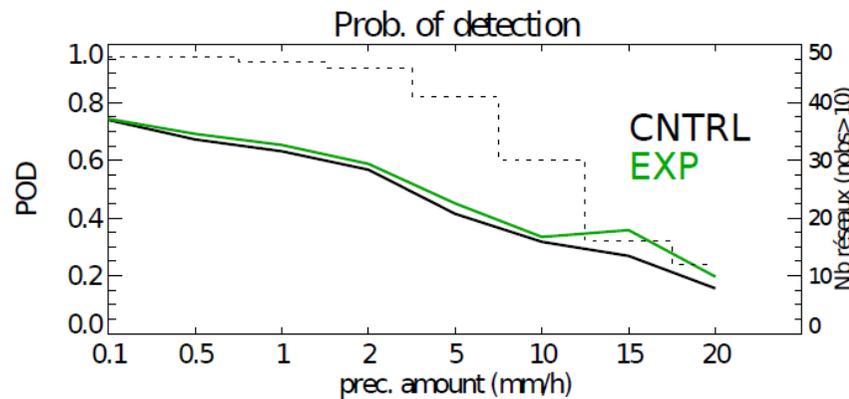
time serie of 12h forecast for q_{850hPa}



Impact on forecasts

Cycled experiment 6 -> 19 June 2010

Scores against raingauges for 3h (top) and 24h (bottom) cumulated rainfall



⇒ Better detection (POD, Brier Skill Score), less bias, neutral on false alarm

Conclusions

The heterogeneous formulation:

- + allows to consider more adequate covariances and balance relationship in areas that are characterized by a specific meteorological phenomena for which forecast errors have been computed
- + if rainy forecast errors are considered, it allows to optimize the use of observations in precipitations and to reduce spin-up
- + slightly positive scores
- as covariances, balance relationships also depend on the meteorological flow, especially in precipitations. Results should be improved in a daily ensemble assimilation framework

Future work will focus on how this approach compares to ensemble assimilation+filtering and to hybrid EnVar approaches using 2D LAM toy models.

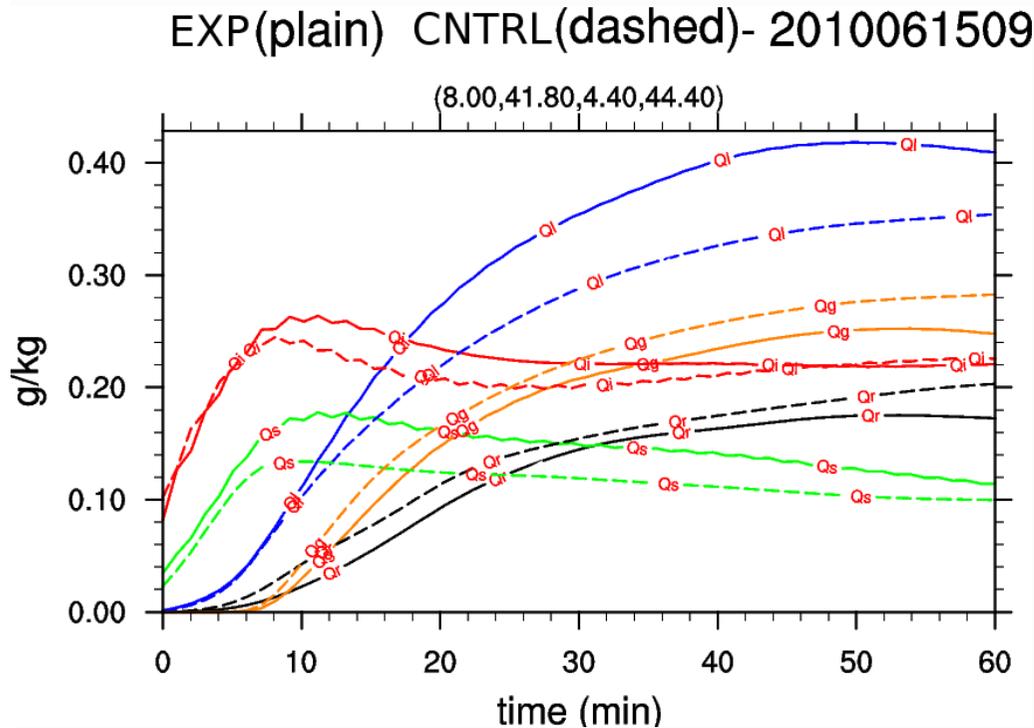
An aerial photograph of a town, likely in a mountainous region, is shown. The town is partially obscured by a thick layer of white clouds or fog. Overlaid on the bottom half of the image is a weather map with white contour lines and arrows indicating wind direction and speed. The contour lines are labeled with values such as 1010, 1015, 1020, 1025, 1030, 1035, and 1040. The background of the entire slide is a deep blue gradient. In the top left corner, there is a small graphic of a sun and clouds. In the bottom right corner, the logo for METEO FRANCE is displayed, featuring a stylized globe icon and the text 'METEO FRANCE' in blue and 'Toujours un temps d'avance' in red below it.

Thank you for
your attention...

References

- Brousseau, P.; Berre, L.; Bouttier, F. & Desroziers, G. : 2011. Background-error covariances for a convective-scale data-assimilation system: AROME France 3D-Var. QJRMS., 137, 409-422
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- Michel, Y., Auligné T. and T. Montmerle, 2011 : Diagnosis of heterogeneous convective-scale Background Error Covariances with the inclusion of hydrometeor variables. Mon. Wea Rev., in press, doi :10.1175/2011MWR3632.1, 2011.
- Montmerle T, Berre L. 2010. Diagnosis and formulation of heterogeneous background-error covariances at the mesoscale. QJRMS, 136, 1408–1420.

Application on real cases: hydrometeors spin-up



For this case, « rainy » forecast error covariances seem to favor the growth of cloudy hydrometeors (q_l , q_i) and q_s to the detriment of precipitating hydrometeors (q_r , q_g).

Mean tendencies on the first hour of simulation for the 15th of June 2010 case averaged on the SE of France



%tage of spinup reduction (2010060818)

